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Review Article

A Survey of Motion Data Processing and Classification Techniques Based on Wearable Sensors

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Abstract

The rapid development of wearable technology provides new opportunities for action data processing and classification techniques. Wearable sensors can monitor the physiological and motion signals of the human body in real-time, providing rich data sources for health monitoring, sports analysis, and human-computer interaction. This paper provides a comprehensive review of motion data processing and classification techniques based on wearable sensors, mainly including feature extraction techniques, classification techniques, and future development and challenges. First, this paper introduces the research background of wearable sensors, emphasizing their important applications in health monitoring, sports analysis, and human-computer interaction. Then, it elaborates on the work content of action data processing and classification techniques, including feature extraction, model construction, and activity recognition. In feature extraction techniques, this paper focuses on the content of shallow feature extraction and deep feature extraction; in classification techniques, it mainly studies traditional machine learning models and deep learning models. Finally, this paper points out the current challenges and prospects for future research directions. Through in-depth discussions of feature extraction techniques and classification techniques for sensor time series data in wearable technology, this paper helps promote the application and development of wearable technology in health monitoring, sports analysis, and human-computer interaction.

Index Terms: Activity recognition, Wearable sensor, Feature extraction, Classification

Introduction

The rapid development of technology and the continuous progress of society have made wearable technology one of the most concerned fields in recent years [1-4]. Wearable devices such as smart watches, smart glasses, health trackers, and smart clothing have gradually integrated into our lives, not only providing us with many conveniences but also giving us more opportunities to obtain data about ourselves and our surrounding environment. Sensors in these devices collect various types of data, including images, sounds, motions, physiological parameters, time series data, etc. [3,5]. Among them, time series data is a particularly challenging type of data because they usually contain a large amount of time series information and require complex processing and analysis techniques to extract useful information.

The rise of wearable sensor technology has greatly benefited from the continuous progress of sensors and the improvement of computing power and storage capacity. Modern wearable sensors are capable of capturing multiple data types, including acceleration, gyroscope, heart rate, skin conductance, temperature, and so on. These sensors monitor various physiological and environmental parameters of the human body in a non-invasive manner, providing strong support for applications such as health monitoring, sports analysis, and the improvement of quality of life [6]. However, the data generated by these sensors is typically multi-channel, high-dimensional time series data with large data volume and complexity. Therefore, the classification techniques for wearable sensor time series data have aroused widespread research interest and received extensive attention in both academia and industry. The efficient processing and analysis of these data to achieve accurate Human Activity Recognition (HAR) has become a challenge.

In the context of wearable sensor data, HAR is an important application area that involves associating data captured by sensors with specific activities or states. Depending on the data type, HAR can generally be divided into two categories: HAR for video data [7-12] and HAR for wearable sensor data [6,13-15].

The method of wearable sensor-based action classification involves using embedded sensors to monitor human movement and physiological parameters. These sensors typically include accelerometers, gyroscopes, heart rate sensors, temperature sensors, etc. By capturing the output of these sensors, multi-channel, high-dimensional data can be constructed for the analysis and classification of different human activities [6]. Camera-based action classification methods use cameras or depth cameras to capture visual information about human movement. These methods typically involve computer vision and image processing techniques to enable real-time monitoring and classification of human posture, and activities [10,12].

Compared to HAR based on wearable sensor data, applications based on video data face multiple challenges. These challenges include the potential risk of user privacy leakage, the fixed position of the camera, the ease with which users can walk out of the camera range, and the large storage requirements for video data [5,16]. Therefore, HAR based on video data has a high demand for data storage and computing resources. In contrast, HAR based on sensor data can effectively circumvent these issues. In addition, the rapid development of mobile terminal hardware technology and Internet of Things technology has made wearable devices more compact, easy to carry, and easy to operate. These devices can be specially designed wearable device sensors for specific tasks, or sensors built into common mobile devices such as smartphones, smart bracelets, game consoles, smart clothing, etc. Compared to video data streams, the volume of sensor data is much smaller. Despite the continuous generation of data by sensors, the network transmission cost and computing cost are relatively low, making it easy to achieve real-time computing. The improvement of the computing power of intelligent terminal devices and the extensive application of remote big data cloud computing platforms have greatly increased the computing speed of applications based on wearable sensors, enabling them to respond to user needs more quickly. Especially in recent years, the development of edge computing has made data processing more efficient. More importantly, sensor data can effectively protect user privacy and reduce the infringement on users' individual characteristics.

Therefore, with the rapid development of technologies such as hardware devices, mobile computing, and artificial intelligence Internet of Things, the HAR applications oriented towards wearable sensor data have gradually increased and been widely applied in daily life, including multiple fields such as health monitoring, entertainment, industry, military, and social interaction [2,4,17].

Health and medical care [18,19]. Wearable technology holds great potential in health monitoring. The emergence of smartwatches, health trackers, and medical devices allows people to monitor vital signs in real-time, such as heart rate, blood pressure, blood oxygen saturation, and body temperature. This real-time data monitoring can alert medical issues in advance and help patients better manage chronic diseases like diabetes and high blood pressure. At the same time, wearable technology is also used in surgical procedures to track patients' vital signs, enhancing surgical safety.

Fitness and sports training [20-22]. Wearable technology has become a valuable assistant for fitness and sports enthusiasts. Smartwatches and sports trackers can monitor exercise data, such as steps, calorie consumption, and sleep quality. This is valuable information for trainers, helping them adjust their training plans to improve effectiveness. In the professional field, athletes can use wearable technology to optimize skills and monitor physical fitness.

Entertainment and gaming [23,24]. Wearable technology offers new possibilities for entertainment forms such as Virtual Reality (VR) and Augmented Reality (AR). VR headsets and AR glasses have been widely used in gaming, virtual travel, and training. They can provide an immersive experience, directly integrating players and users into the virtual world.

Production and industrial fields [25,26]. In the manufacturing and industrial fields, wearable technology helps to improve efficiency and safety. For example, smart glasses can provide real-time information and guidance to workers, helping them complete complex tasks. Sensors embedded in workwear can monitor the posture and movements of employees to prevent injuries.

In conclusion, wearable technology has profoundly changed our way of life, providing more convenience, safety, and interactivity. Their application in multiple fields continues to drive technological innovation, indicating that we will continue to see more exciting development and improvement in the future. The continuous progress of these technologies will bring more possibilities to our lives, promoting the development of health, entertainment, productivity, and social interaction.

Generally, the classification technology of wearable sensor time series data is summarized as the HAR basic framework as shown in Figure 1, which mainly includes three core modules, namely feature extraction, model construction, and activity recognition. By learning the feature vectors of human activities and actions from wearable sensor time series data through feature extraction, models are learned and constructed according to different application requirements, and user action categories are identified in practical applications using trained models. Based on this, this paper focuses on a comprehensive review of the development of classification technology for wearable sensor time series data, focusing on the feature extraction technology of wearable sensor time series data, time series classification models, and current challenges, in order to help researchers better understand the current situation and future development trends in this field.

Feature extraction

The goal of feature extraction is to find features that can express different activities so that they can be used for action discrimination in sensor data classification techniques. This field is currently one of the research hotspots. A good feature expression has a significant impact on the classification accuracy of the model. Sensor data, mainly from triaxial inertial sensors such as accelerometers, gyroscopes, and magnetometers, are used to construct these features.

As shown in Figure 1, preprocessing of the original data is a

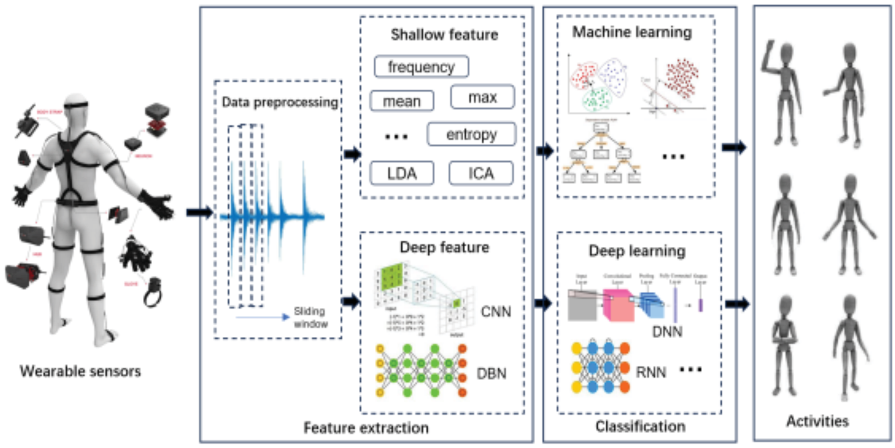

Figure 1: The basic framework of HAR is based on sensor time series data classification technology.

necessary step before constructing the feature space, aimed at reducing noise data in the original data and slicing time-series data according to the window size. First, the original data is processed through a filter to reduce noise points and normalize the data within a certain period of time. Next, the data is segmented according to a fixed window size, and the time-series sensor data within each window is regarded as a processing sample unit for activity recognition [27]. Typically, longer-lasting actions use larger time windows, while shorter actions use smaller time windows. The size of the sliding window is typically determined by the activity category and the data sampling frequency. A large window may contain multiple short-term activity categories, while a small window may result in incomplete actions [28,29].

According to the way features are generated, features in the HAR framework can be divided into two categories: traditional features and deep features [30,31]. Shallow features are features manually extracted based on statistical methods, while deep features are features automatically extracted based on neural networks, etc.

Shallow feature extraction

The traditional features mainly rely on empirical knowledge and require artificial extraction of statistical significance feature vectors from the partitioned data, including time-domain features [32], frequency-domain features [33], and other features [14,34]. Among them, time-domain features mainly include mean, variance, standard deviation, skewness, kurtosis, quartiles, mean absolute deviation, and correlation coefficients between axes; frequency-domain features mainly include peaks, energy, and discrete cosine transform of the discrete Fourier transform spectrum; wavelet features are approximate wavelet coefficients and detailed wavelet coefficients obtained after discrete wavelet transform and these features are shown in Table 1.

The method of manual feature extraction is explanatory, easy to understand, and low in computational cost. However, for complex actions, the expressiveness of traditional features is limited, which affects the recognition effect of the model. In the research on human action recognition based on wearable sensors, researchers have used various feature extraction methods and classification techniques to solve this problem. The following are some representative research methods: Altim, et al. [35] used time-domain features such as mean, variance, skewness, kurtosis, and the correlation coefficients between axes, and compared the performance of different classification techniques. Zhang, et al. [36] extracted time-domain features such as mean, quartiles, and skewness, and used sparse representation algorithms for action classification. Bao, et al. [37] used time-domain features such as mean, correlation coefficients between axes, and peaks and energies of the Discrete Fourier Transform spectrogram to identify 20 daily actions. Altun, et al. [38] used frequency-domain features based on Discrete Cosine Transform for action classification in another study. Khan, et al. [39] used autoregressive models and extracted features such as autoregressive coefficients and the inclination angle of the body for action recognition.

Table 1: Feature types in action recognition tasks.

Feature Type	Description
Time Domain Features	mean, variance, skewness, maximum value, minimum value, peak value, zero-crossing rate, kurtosis, etc.
Frequency Domain Features	Spectral peak value, energy, Fourier transform, median frequency, information entropy, etc.
Other Features	Wavelet coefficients, IMF decomposition coefficients, etc.

After extracting these features, researchers usually face a high-dimensional feature vector, which may lead to high computational complexity, insufficient data intuitiveness, and poor visibility. Therefore, feature dimensionality reduction is necessary to eliminate redundant information in the data. In sensor-based human action recognition research, common feature dimensionality reduction methods include Principal Component Analysis (PCA) [40-42], Linear Discriminant Analysis (LDA) [43,44], and Independent Component Analysis (ICA) [45,46], etc.

The core idea of PCA [40-42] is to project high-dimensional data into a low-dimensional space while preserving as much information as possible. This is achieved by calculating the covariance matrix and eigenvalues, and then arranging the feature